Patterns of Inquiry, Scaffolding, and Interaction Profiles in Learner-AI Collaborative Math Problem-Solving

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Abstract

This study investigates inquiry and scaffolding patterns between students and MathPal, a math AI agent, during problem-solving tasks. Using qualitative coding, lag sequential analysis, and Epistemic Network Analysis, the study identifies distinct interaction profiles, revealing how personalized AI feedback shapes student learning behaviors and inquiry dynamics in mathematics problem-solving activities.

1 Introduction & Background

As generative artificial intelligence (GAI) becomes increasingly integrated into K–12 settings, educators and researchers are starting to explore how GAI tools can meaningfully support student learning through interactive, adaptive assistant (Lang et al., 2025). Recent studies have shown that conversational AI tools can act as learning companions, offering personalized scaffolding and guiding students through complex tasks in real time, particularly in K–12 contexts (Kim & Kwon, 2025; Li et al., 2024). In mathematics education, where students often struggle with abstract reasoning and procedural complexity in the subject such as algebra, AI agents have the potential to provide personalized, real-time feedback that bridges the gap between instruction and independent inquiry.

The idea of instructional scaffolding has long emphasized the importance of timely support that is tailored to the learner's evolving needs (Belland, 2017). In AI-integrated learning environments, scaffolding can take the form of prompts, hints, motivational encouragement, or step-by-step guidance, each playing a crucial role in sustaining engagement and deepening understanding especially as students are solving math problems independently (Rittle-Johnson & Koedinger, 2005; Tay & Toh, 2023). Similarly, inquiry-based learning frameworks have highlighted how students' questioning behaviors, exploration strategies, and reflection processes contribute to meaningful learning (Artigue & Blomhøj, 2013). Yet, less is known about how these two dynamics—inquiry and scaffolding—manifest when students interact with AI agents in real-time problem-solving contexts.

This gap calls for a closer examination of how AI-mediated interactions shape learning processes in mathematics, particularly how students and ai agents collaboratively navigate complex problem-solving tasks. While previous studies have demonstrated the effectiveness of intelligent tutoring systems in enhancing performance and engagement (Niño-Rojas et al., 2024; Zhang & Jia, 2017), relatively few have examined the dialogic and adaptive qualities of these interactions—particularly from the dual perspectives of student-initiated inquiry and AI-

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generated scaffolding. Moreover, although some work has explored AI's responsiveness to student input (Atherton et al., 2024; Kim et al., 2025), there remains a lack of fine-grained analysis on how specific types of student inquiries elicit particular forms of scaffolding, and how these patterns vary across learners.

To address this gap, this study examines how high school students interact with MathPal (MathPal, 2023), an AI conversational agent designed to provide personalized support during math problem-solving tasks. Grounded in growth mindset and dialogic learning principles, MathPal engages students through structured yet adaptive conversation, offering hints, strategies, and encouragement as they work through algebraic problem sets. The integration of MathPal into real classroom settings offers a rich opportunity to explore the nature of AI-mediated learning interactions and to better understand how students navigate mathematical problem-solving tasks colligatively with an AI agent.

This research is guided by two key aims. First, researchers seek to analyze the patterns of inquiry and scaffolding interactions that emerge during student–MathPal problem-solving conversations. By classifying the types of questions students pose and the forms of support provided by AI, researchers aim to identify recurring patterns and interactional flows that characterize the learning dialogue. Second, this study intends to investigate how students differ in their interaction trajectories with MathPal, and whether distinct profiles of interaction can be identified across the classroom. Understanding these profiles may help educators and designers develop more adaptive AI systems that tailor scaffolding strategies to students' unique learning needs and inquiry styles, which lead to the following two research questions:

RQ1: What are the patterns of inquiry and scaffolding interactions between students and MathPal during math problem-solving activities?

RQ2: What distinct student interaction profiles with MathPal emerge during math problem-solving, and how do these profiles reflect differences in learning behaviors?

2 Methods

2.1 Participants

Participants were 48 ninth-grade students enrolled in three Algebra I classes at an urban high school located in the northeastern United States. The school serves a diverse student population with approximately 50% of students identified as economically disadvantaged. All participants were taught by the same high school mathematics teacher who has 12 years of teaching experience. Teacher consent, parental permission, and student assent were obtained in accordance with Institutional Review Board (IRB) approval prior to the commencement of the study and data collection.

2.2 Math AI Agent--MathPal

MathPal is an AI-powered conversational agent designed to serve as an interactive math learning partner for high school students. It supports students in understanding mathematical concepts and offers strategies and hints to guide them in solving practice problems. Informed by growth mindset concept (Dweck, 2006), which is the belief that abilities can be developed through effort, effective strategies, and constructive feedback, MathPal encourages students to persist through challenges and view mistakes as opportunities for learning.

MathPal can be integrated seamlessly with digital math learning platforms, providing students with real-time, responsive guidance in a conversational and supportive tone. Its design promotes resilience and confidence in problem-solving by offering personalized support aligned with students' learning needs. As shown in Figure 1, MathPal can read the screen and assist students in solving problems by providing strategies or hints without revealing the answer, using growth mindset–aligned language to facilitate problem-solving process.

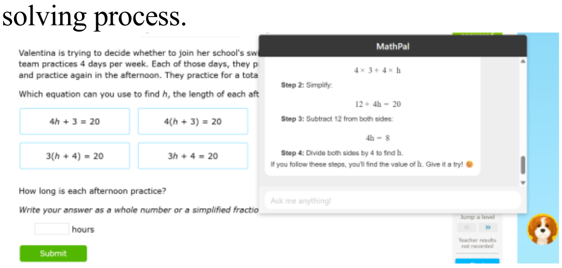

Figure 1: MathPal Conversation Interface

Additionally, MathPal promotes focus and motivation by redirecting off-topic discussions toward relevant mathematical content, linking students' personal interests to core math concepts. When students interact with MathPal, whether to ask about algebraic concepts or problem-solving steps and strategies, their inputs are interpreted by the system, routed through reliable back-end computational engines, and reformulated into accessible and student-friendly language.

2.3 Research Contexts

MathPal was integrated into the 9th-grade Algebra I curriculum and embedded within a virtual mathematics learning program. During daily math lessons, following the teacher's instruction, students transitioned to the virtual program for individual practice, typically engaging in math problem sets for approximately 15–20 minutes per class session. As students worked through various problem-solving tasks, they interacted with MathPal to receive guidance and tailored feedback. The types of tasks and instructional content supported by MathPal were aligned with daily instructional concepts such as solving linear function problems.

At the beginning of the semester, teachers provided an on-boarding session to students on installing and using MathPal, including demonstrations of its features and functions. Students then utilized MathPal throughout the semester (14 weeks) as a regular component of their mathematics learning experience (see Figure 2). During independent practice, teachers circulated around the classroom to address students' questions, whether related to the use of MathPal or the mathematical content itself. This support ensured that students remained engaged and could navigate the problem-solving tasks effectively.

Figure 2. Daily Math Lesson with MathPal

2.4 Data Analysis

Qualitative analysis was used to examine the conversational exchanges between students and MathPal during problem-solving activities. A total of 1,214 conversational threads were generated by the 48 participating students.

To better understand how students interact with MathPal during problem-solving activities, an inductive approach to qualitative analysis was used. Because engaging with an AI agent to solve problems collaboratively is a first-time experience for many students, the goal was to allow inquiry patterns to emerge directly from the data. Accordingly, open coding was first applied to identify recurring concepts and types of student input, followed by axial coding to organize these codes into broader themes and subthemes representing students' engagement with the tool (Strauss & Corbin, 1998). The researchers independently coded the first 300 threads of the data and developed separate codebooks. Through a process of comparison, contrast, and triangulation, they reconciled differences and collaboratively refined the codes into a single, unified codebook. This final codebook was then applied to complete the coding of the full dataset. Table 1 presents the codebook used to categorize students' inquiry types during problem-solving interactions. These were classified into five categories: solution-focused, conceptual, computational, formula/procedural, and clarification-seeking inquiries.

Theme	Definition	Example
Clarification Seeking	Students ask for repetition, elaboration, or clearer explanation of problem-solving process.	Can you go through the steps again?
Computational Inquiry	Students inquire about performing a specific mathematical computation.	I need to calculate cos(π/4) without a calculator.
Conceptual Inquiry	Students seek to understand the underlying meaning behind a mathematical concept.	What exactly is a derivative.
Formula/ Procedural Inquiry	Students ask for a formula, rule, or step-by-step procedure for solving a problem.	Can you provide the steps for computing the determinant.
Solution-Focused Inquiry	Students directly request help in solving a specific problem.	Can you help me solve this equation

Table 1. Codebook for Student Inquiry Types

To better understand how MathPal supported students in progressing through the problem-solving process, a deductive coding analysis (Fereday & Muir-Cochrane, 2006) was conducted on the AI-generated responses to student inquiries. The coding scheme was adapted from the STEM scaffolding types proposed by Belland (2017), which enables researchers to capture diverse forms of cognitive, metacognitive, and strategic support essential to inquiry-based learning, thus aligns well with the problem-solving context of this study. Researchers followed a similar coding and triangulation process as used in the student data analysis, collaboratively refining and consolidating the codebook through consensus (see Table 2).

Theme	Definition	Example
Conceptual Scaffolding	Provides explanations or definitions to help students understand underlying mathematical concepts.	A linear function is a function that…
Manage-ment Scaffolding	Help students stay on task or maintain focus during the problem-solving process.	Let's focus on solving the math problem!
Metacog-nitive Scaffolding	Encourages students to reflect on their thinking, or self-monitor their problem-solving process.	Let's go through this again…Ve-rify these to ensure correctness. Let me know how that works out.
Motivation-al Scaffolding	Offers encourage-ment or support to sustain students' confidence or engagement in the learning task.	I'll provide you with hints and guidance. Let's work together on some math problems!
Strategic Scaffolding	Guides students through a step-by-step process or strategy to solve a problem effectively.	To solve the problem of……., follow these steps……

Table 2. Codebook for MathPal's Scaffolding Types

After completing the coding of both students' and MathPal's data based on the established codebook, data visualization and lag sequential analysis were conducted to address the first research question, which focused on the temporal patterns of inquiry types during problem-solving interactions.

To address the second research question, Epistemic Network Analysis (ENA; Shaffer, 2017) was employed to examine the co-occurrence and structural patterns of student–AI interactions. ENA utilizes a sliding window (also referred to as a "stanza") to analyze interaction data, enabling the identification of codes that co-occur frequently within a defined context. In this study, the unit of analysis for ENA was the individual student, with each student's interaction history with the AI defined as "conversation". For this analysis, the stanza size was set to seven, a standard parameter commonly used for modeling conversational data.

Following the initial ENA modeling, K-means clustering was applied to uncover distinct patterns of student-AI interaction. Using students' network projections on the ENA plane, the K-means algorithm was employed to determine the optimal number of clusters, ensuring that within-cluster similarity was maximized while between-cluster similarity was minimized. Subsequently, the clustering results were integrated into the ENA modeling to visualize and compare student-AI interactions across the identified clusters.

3 Results

3.1 RQ1: Inquiry and Scaffolding Patterns During Problem-Solving

To gain a comprehensive understanding of the general interaction patterns between students and MathPal, pie charts were created to illustrate the distribution of student inquiry types and MathPal's scaffolding strategies. Figure 3 reveals that Solution-Focused Inquiry accounted for the largest proportion of student utterances (42.29%), followed by Computational Inquiry (20.48%). This indicates that students primarily engaged with MathPal when tackling multi-step tasks or performing calculations. For example, a student asked, "how to do this problem step by step," which reflects a focus on procedural progression rather than conceptual exploration.

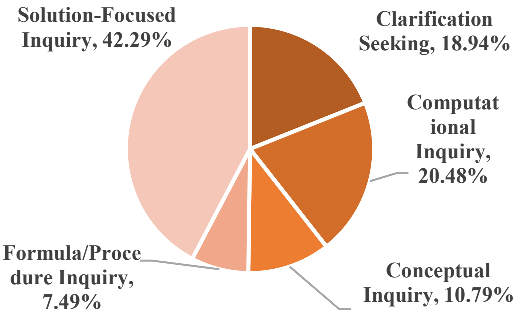

Figure 3: Student Inquiry Type Distribution

On MathPal's side (Figure 4), Strategic Scaffolding was the most frequently applied support type (52.88%), emphasizing the system's tendency to guide students through structured problem-solving steps. Together, the pie charts suggest that student-AI interactions were heavily oriented toward procedural assistance, with MathPal primarily functioning as a step-by-step guide rather than a conceptual tutor. This raises important pedagogical considerations for designing AI that not only supports task completion but also fosters deeper mathematical understanding.

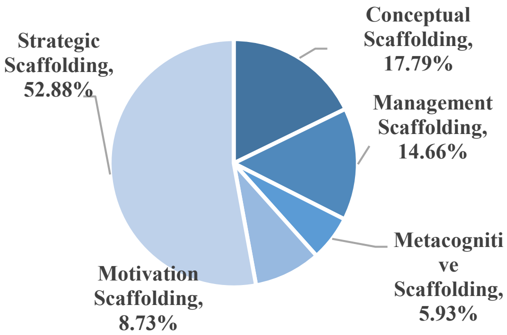

Figure 4: MathPal Scaffolding Type Distribution.

To further illuminate how specific types of student inquiries elicited corresponding scaffolding from MathPal, a Sankey diagram was constructed to visualize the directional flow of interactions between learner input and MathPal-generated scaffolding. This diagram captures the distribution of coded interactions across 454 episodes, illustrating how the nature of student queries on the left influenced the form of scaffolding provided on the right.

As indicated in figure 5, the dominant flow in the diagram stems from Solution-Focused Inquiry (n = 192), which overwhelmingly leads into Strategic Scaffolding (n = 300). This directional flow demonstrates that when students present complex problem-solving questions, such as those requiring multi-step reasoning, MathPal responded primarily with strategic procedural guidance. A typical case illustrates this flow: a student asked, "how to do this problem step by step", which was answered with: "To solve the equation -8d + 11d = 9d, follow these steps...". Such flows underscore the alignment between problem complexity and strategic decomposition in AI support, suggesting that MathPal's scaffolding logic is tightly calibrated to respond to problem-solving requests.

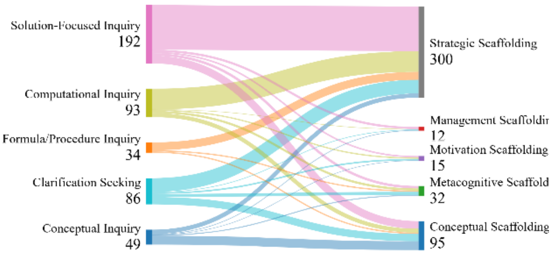

Figure 5: Student Inquiry Types and Corresponding MathPal Scaffolding Support

Computational Inquiries (n = 93) also predominantly flowed toward Strategic Scaffolding. The directional thickness of this stream in the Sankey diagram reflects frequent AI responses aimed at operational clarity. For example, queries like "put 10, 20,15, 30... in a number line" prompted responses emphasizing ordered thinking, reinforcing the trend that MathPal prioritizes task structure and planning in response to numerical and operational queries.

Another substantial pathway leads from Clarification Seeking (n = 86) and Conceptual Inquiry (n = 49) into Conceptual Scaffolding (n = 95). These flows signify situations where learners express epistemic uncertainty, often about definitions, categories, or relational understanding, and the AI responded with conceptual elaboration. This pattern affirms that conceptual depth on the part of the student correlates with knowledge-level scaffolding from MathPal, further evidencing a pedagogically aligned flow system.

In contrast, weaker flows were observed toward Management (n = 12), Motivational (n = 15), and Metacognitive Scaffolding (n = 32). These less prominent flows appeared thin across all inquiry types, indicating either low incidence of such student needs or limited detection and activation by MathPal. Notably, even from Solution-Focused Inquiries, which is the most dominant source, only a small number of instances flowed into these support categories.

The visual marginality of these flows in the Sankey chart, particularly those leading to motivational, management, and metacognitive scaffolding, points to instructional dynamics where motivational and self-regulatory supports are engaged less frequently in AI-student interactions.

In summary, the Sankey diagram functionally maps the dialogic flow from student-generated inquiries to AI-generated scaffolds, offering a visual representation of how MathPal interprets and responds to varying learner needs. The flow patterns reveal a predominant reliance on strategic and conceptual scaffolding, primarily triggered by Solution-Focused and Clarification-Seeking inquiries, respectively. The directionality and volume of these flows underscore the AI's responsiveness to cognitive and procedural challenges. From an instructional perspective, these patterns invite further consideration of how scaffolding models might be expanded to proactively integrate motivational and metacognitive supports, particularly in contexts where student engagement, persistence, or reflection could enhance learning outcomes.

While the Sankey diagram visualizes aggregate inquiry–scaffolding flows, it does not test whether specific patterns are statistically significant. To investigate these patterns systematically, we conducted a Lag Sequential Analysis to examine whether specific types of student inquiries consistently elicited particular AI scaffolds in a statistically meaningful way. This analysis examined the extent to which specific student inquiry types were predictably followed by particular MathPal scaffolding beyond what would occur by chance. By statistically modeling these turn-by-turn sequences, we were able to identify significant dialogic contingencies that provide deeper insight into the dynamics of student–AI interaction during problem-solving.

The results from lag-sequential analysis revealed statistically significant patterns of interaction between students and MathPal during high school mathematics problem-solving activities. As summarized in Table 3, each student inquiry type was followed by distinct forms of AI scaffolding at rates significantly higher than expected by chance ($z > 1.96$, $p < .05$). For example, Problem-Solving Inquiries were most frequently followed by Strategic Scaffolding ($z = 10.54$) and Management Scaffolding ($z = 10.48$), suggesting that MathPal responds to action-oriented problem-solving attempts by providing procedural guidance and task organization support—both of which are essential for success in secondary-level mathematics.

Inquiries focused on formulas and procedures led to similarly strong responses, particularly Strategic Scaffolding ($z = 9.38$) and Metacognitive Scaffolding ($z = 6.71$), reflecting MathPal's tendency to blend step-by-step guidance with prompts for reflection. Conceptual Inquiries elicited Conceptual Scaffolding ($z = 5.93$), indicating that MathPal adjusts to cognitively deeper questions with explanation-focused support. Additionally, Clarification-Seeking moves triggered a broad range of responses, including Conceptual ($z = 4.40$), Metacognitive ($z = 4.05$), Strategic ($z = 4.00$), and Motivational Scaffolding ($z = 3.77$), showing that the AI detects confusion as an opportunity for multi-dimensional support.

Overall, the results highlight MathPal's capacity to align its scaffolding strategies with the nature of student input, supporting the notion of contingent scaffolding in AI-driven learning environments, particularly within high school mathematics problem-solving contexts.

Student Inquiry	**MathPal Scaffolding**	**Z-Score**
Solution-Focused Inquiry	Strategic Scaffolding	10.54
Solution-Focused Inquiry	Management Scaffolding	10.48
Formula/Procedure Inquiry	Strategic Scaffolding	9.38
Formula/Procedure Inquiry	Metacognitive Scaffolding	6.71
Conceptual Inquiry	Conceptual Scaffolding	5.93
Computational Inquiry	Strategic Scaffolding	4.99
Computational Inquiry	Metacognitive Scaffolding	4.62
Computational Inquiry	Motivation Scaffolding	4.44
Clarification Seeking	Conceptual Scaffolding	4.40
Clarification Seeking	Metacognitive Scaffolding	4.05
Clarification Seeking	Strategic Scaffolding	4.00
Clarification Seeking	Motivation Scaffolding	3.77

Table 3: Significant Transitions Between Student Inquiry Types and MathPal Scaffolding

3.2 RQ2: Student-AI Collaborative Problem-Solving Profiles

While lag sequential analysis uncovered statistically significant turn-level patterns between inquiry types and scaffolding responses, it does not reveal how these interaction patterns accumulate across learners. To address this, we employed Epistemic Network Analysis (ENA) to model individual students' inquiry–scaffold co-occurrence structures and identify latent profiles of interaction. ENA diagrams were developed to better understand students-MathPal collaboration patterns during problem-solving activities. As shown in Figure 6, the dots represent the projections of individual student networks , while the square markers indicate the average projections of students within each cluster. The spatial distances within the ENA diagram reflect differences in network structures, where closer dots indicate more similar interaction patterns, and greater distances signify more distinct structures. ENA analysis revealed four distinct interaction clusters, corresponding to different patterns of student-MathPal interactions.

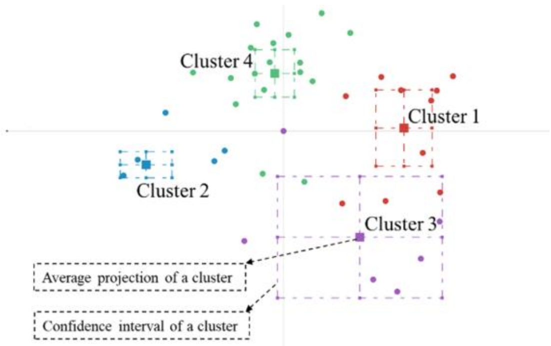

Figure 6: Distributions of four clusters of student-AI interactions

The specific connection patterns within each cluster, visualized in Figure 7, further illustrate these distinctions. In Cluster 1, the strongest connection was observed between computational inquiry and strategic scaffolding. Meanwhile, there were several moderate connections such as clarification seeking-strategic scaffolding and solution-focused inquiry-strategic scaffolding. Comparatively, the most prominent connection in Cluster 2 was between solution-focused inquiry and strategic scaffolding, suggesting a goal-driven interaction pattern. In contrast, Cluster 3 exhibited more balanced connections overall, with a slightly stronger connection between strategic scaffolding and motivation scaffolding. Lastly, Cluster 4 featured prominent connections among solution-focused inquiry, computational inquiry, and strategic scaffolding, as well as a moderate connection between solution-focused inquiry and conceptual scaffolding, suggesting a blend of conceptual understanding and problem-solving strategies.

Each cluster reflects an integrated pattern of how students regulate their interactions with MathPal and their learning. By identifying these clusters (and more importantly their specific configurations), we can provide students with personalized support and also identify students who are not engaging with MathPal effectively in Problem-solving activities.

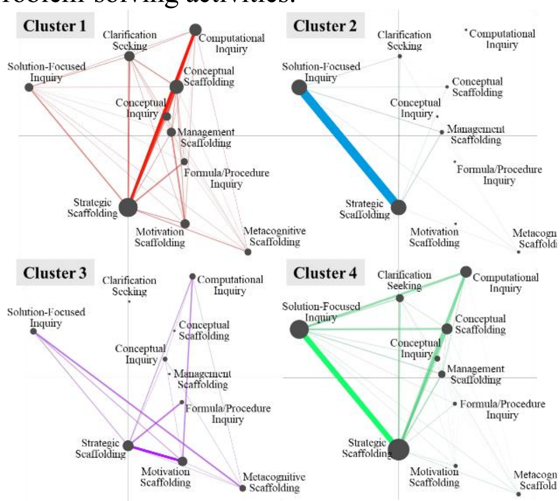

Figure 7: Four types of student-AI interaction patterns

4 Discussion & Implications

This study examined how students interacted with MathPal, an AI-based scaffolding tool, during math problem-solving. Two core findings emerged: (1) students followed consistent inquiry–scaffolding patterns centered on procedural support, and (2) distinct student–AI collaborative problem-solving profiles reflected varying learning behaviors. These findings extend current research on AI tutoring systems (Holstein et al., 2019) and offer new insight into how generative AI can be adapted for more personalized, effective learning support in math problem-solving contexts.

4.1 Personalizing AI Scaffolding Based on Student Inquiry

Most student inquiries were solution-focused or computational, prompting primarily strategic scaffolding from MathPal. While this guided students through procedural tasks, it offered less conceptual or motivational support. This imbalance suggests AI agents should better detect moments of confusion or disengagement to deliver metacognitive or motivational scaffolds.

The findings align with the idea of contingent scaffolding, which emphasizes the need for support to be responsive to students' evolving cognitive and affective states (Van de Pol et al., 2010). Enhancing AI systems with adaptive feedback mechanisms that dynamically shift between strategic, conceptual, and motivational scaffolding may promote deeper learning by moving students beyond surface-level task completion toward the development of enduring mathematical understanding and problem-solving skills (Aleven et al., 2016).

4.2 Personalizing Support Through Interaction Profiles

The distinct interaction profiles offer actionable insights for designing more personalized and effective AI learning support. By recognizing students' habitual inquiry patterns, AI systems can adapt their scaffolding strategies to align with individual cognitive and motivational needs. For instance, students who primarily engage in procedural or solution-focused exchanges may require targeted prompts that promote self-explanation, conceptual elaboration, or metacognitive reflection (Belland, 2017). Conversely, students exhibiting more exploratory or conceptual dialogue might benefit from strategic scaffolds that help organize their thinking and support knowledge gaining. Such adaptive tailoring not only supports differentiated learning trajectories but also enables educators to detect patterns of disengagement or superficial inquiry and intervene to promote deeper engagement and sustained learning growth (Roll & Winne, 2015).

4.3 Theoretical and Methodological Perspectives

From a theoretical lens, the findings align with socio-cognitive perspectives that view learning as a co-constructed process. In the context of this study, students and the AI agent collaboratively constructed knowledge to complete problem-solving tasks through dialogic interaction, learner-driven inquiry, and scaffolded support (Mercer & Howe, 2012). The observed variation in student–AI interaction patterns highlight the importance of context-sensitive scaffolding, reinforcing prior work that emphasizes the dynamic and situated nature of collaborative learning with intelligent tools (Sawyer, 2014). These profiles not only reflect variation in students' inquiry behaviors but may also signal different AI scaffolding patterns in math problem-solving contexts.

Methodologically, this study demonstrates the value of combining qualitative coding with lag sequential analysis and ENA to capture both the structure and flow of human–AI interaction. ENA, in particular, proved effective in visualizing co-occurring patterns that distinguish learner engagement types. The use of clustering to define emergent profiles further enhances ENA's utility in learning analytics, offering a powerful lens for exploring personalized learning trajectories in real-world settings.

5 Conclusion

This study explored how high school students interact with a math AI agent, MathPal, during problem-solving activities. Findings revealed consistent patterns of inquiry and scaffolding, with students frequently seeking procedural help and the AI responding primarily with strategic guidance. Through ENA, four distinct interaction profiles emerged, reflecting differences in how students engage with AI support. These results highlight the need for adaptive AI scaffolding that responds not only to task demands but also to learners' conceptual and motivational needs. By leveraging interaction patterns, educators and designers can create more personalized, responsive AI systems that better support students' math learning in high school classrooms.

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